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The Long Memory Model of Political Support: Some Further Results

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The Long Memory Model of Political Support: Some Further Results

Abstract

This paper extends the results of Byers, Davidson and Peel (1997) on long memory in support for the Conservative and Labour Parties in the UK using longer samples and additional poll series. It finds continuing support for the $ARFIMA(0,d,0)$ model though with somewhat smaller values of the long memory parameter. We find that the move to telephone polling in the mid-1990s has no apparent effect on the estimated value of d for either party. Finally, we find that we cannot reject the hypotheses that the parties share a common long memory parameter which we estimate at around 0.65.

Keywords: Fractional Integration, Long Memory, Opinion Polls, Partisanship, Political Support

JEL Classification: C22, D72

Introduction

Byers, Davidson and Peel (1997, 2002) - hereafter BDP - proposed a long memory model of aggregate support for political parties and estimated it using Gallup poll data for the Conservative and Labour parties in the UK. Measuring political support by the expressed intention to vote for a particular party, the approach relies upon explicit aggregation of individual support to derive an aggregate function in which the influence of events on party support is highly persistent. Analysis of data on a number of parties in other countries in Byers, Davidson and Peel (1999) provided further support for the model. Appealingly, for almost all parties considered, a simple one parameter model with uncorrelated innovations captured the observed intertemporal dependence in political popularity. Formally, the series can be adequately modelled as pure fractionally-integrated processes with long memory parameter, d . This parameter indexes the rate at which the influence of 'shocks' to support decline over time. Box-Steffensmeier and Smith (1996) estimate a similar model for the USA and obtain similar results as do Dolado *et al* for Spain

This paper extends the earlier results for the Conservative and Labour parties in the UK. Firstly, we extend the sample period. The original paper used the Gallup 'Snapshot' series for the period September 1960 to May 1995. In this paper we use data from January 1948 to December 2000, the longest regularly sampled series of Gallup data available. Secondly, the passage of time means that samples of reasonable size are now available for the voting intentions surveys carried out by ICM and MORI. This enables us to estimate the BDP model on data obtained by different organisations and using alternative sampling methods. In particular,

we can compare the values of d obtained from these pollsters and investigate whether the move from quota sampling to telephone polling by two of the three organisations in the middle of the 1990s has any effect on its estimated value. Thirdly, we use a multivariate approach on a common sample of Gallup and MORI data to test for equality of the long memory parameter across parties and organisations.

The Model

Party allegiance is a binary variable: an individual either supports a political party or does not. Some allegiances are strong and others are fickle but whatever the degree of attachment it will be revised in the light of events which provide evidence on whether the existing commitment is justified or not. Let x_t^i be a variable which takes the value 1 in any time period, t , when individual i supports Party X and zero otherwise. If micro-level panel data were available we would observe for each individual sequences of ones and zeros. A highly committed voter would exhibit long sequences of ones interspersed with short sequences of zeros, or vice versa, while a voter with a low degree of attachment would exhibit alternating short sequences of ones and zeros. Aggregate support for Party X in period t can be measured as the average value of x_t^i - the proportion of voters favouring Party X . Opinion polls provide estimates of this population variable.

Support can also be expressed in terms of p_t^i , the probability that $x_t^i = 1$ and the expected value of x_t^i . Whereas x_t^i is insensitive to current news except when accumulated experience causes it to flip from zero to one or vice versa, the probability, p_t^i , can be thought of as responding continuously to the flow of

events. A significant problem in using p_t^i as the central variable of the analysis is that it is constrained to lie between zero and one. To avoid this the BDP model uses the log-odds ratio,

$$y_t^i = \ln \left(\frac{p_t^i}{1 - p_t^i} \right) \quad 0 \leq p_t^i \leq 1$$

As p_t^i goes from zero to one, y_t^i varies between minus infinity and plus infinity.

However, the response of y_t^i to p_t^i is much larger towards the extremes. The log-odds ratio is zero when p_t^i is 0.5 and around this value the transformation is approximately linear.

A simple model for the evolution of the log-odds ratio at the level of the individual is the first order autoregressive process,

$$y_t^i = \alpha_0^i + \alpha^i y_{t-1}^i + \varepsilon_t^i$$

where i denotes the individual, $0 \leq \alpha^i < 1$ and ε_t^i is a random shock representing ‘news’. Notice that the news variable is individual specific – the same piece of information can be good news to some individuals and bad news to others. The expected value of y_t^i is

$$E(y_t^i) = \frac{\alpha_0^i}{1 - \alpha^i}$$

If $\alpha^i \approx 0$, $E(y_t^i) \approx \alpha_0^i$. If $\alpha_0^i = \alpha^i = 0$ the expected probability of supporting

Party X is 0.5. At the other extreme if $\alpha^i \approx 1$, $E(y_t^i)$ will, depending on the sign

of α_0^i , tend to either a very large positive number or a very large negative number so the probability of supporting Party X will either be close to one or close to zero.

We can characterise voters by the way they respond to news or, equivalently, by the responsiveness of p_t^i to changes in y_t^i . When p_t^i is close to either zero or one even quite substantial changes in y_t^i will have relatively little effect on the probability of supporting Party X . Responsiveness of p_t^i to y_t^i is largest at $p_t^i = 0.5$. Hence, we can think of individuals with $\alpha^i \approx 0$ as floating voters and individuals with $\alpha^i \approx 1$ as committed voters. The restriction that α^i is strictly less than one implies that, absent new shocks, an individual's party support would eventually return to some value, $E(y_t^i)$, which is independent of the previous history of news and which reflects a preference for some particular position on the political spectrum. Individuals with $\alpha^i = 1$ would simply stick with the political views which they had when the shock process was turned off. Excluding this possibility means that, at the individual level, party support is mean reverting.

The fact that the log-odds ratio for each individual voter is autoregressive of order 1 does not imply that aggregate support for Party X has a similar property. In fact, it depends on the distribution of α^i in the population of voters. The BDP model exploits a result by Granger that when the α^i coefficients are randomly drawn from a Beta(u, v) distribution the panel average of a large number of $AR(1)$ processes has a moving average representation in which the MA coefficients decline hyperbolically rather than exponentially. Consequently, the evolution of

aggregate support cannot be adequately modelled by a stationary *ARMA* process. Instead, aggregate party support, s_t , will follow a fractionally integrated process of the form

$$s_t = (1 - L)^d z_t$$

where z_t is a stationary stochastic process and $d = 1 - \nu$. The important practical implication of this result is that the effect of a piece of good or bad news on aggregate party support diminishes at a much slower rate than its effect on individual support would suggest. Aggregate support has a ‘long memory’ property which is lacking in individual support.

The Data and Estimation Procedures

The data analysed here are the log-odds ratios of monthly series on voting intentions carried out by Gallup, ICM and MORI. Each of these organisations asks a similar question to gauge support for the various parties. For instance, Gallup’s question is ‘If there were a General election tomorrow, which party would you vote for?’ Those answering ‘Don’t Know’ are asked to indicate which party they would be most inclined to vote for and the figures are then adjusted to add up to 100%. For our purposes the various technical issues which are used in the attempt to ensure that the sample is properly representative of the population as a whole are not immediately relevant though it should be noted that the published figures often include adjustments designed to improve the performance of a poll as a forecast of electoral outcomes and so are not the ‘raw’ numbers.

The Gallup data is taken from King and Wybrow (2001). The continuous monthly series starts in January 1948 and ends in December 2000. The MORI

series starts in August 1979 and continues to be available. The data is taken from the MORI website (<http://www.mori.com/polls/trends.shtm>). The ICM series runs on a continuous basis from December 1987 and was taken from the ICM polls archive (<http://www.icmresearch.co.uk/reviews/polls-archive.asp>). In the case of the latter two polls, the sample terminates at April 2005. Although we use the word ‘continuous’ there are, in fact, gaps in all of the polls in the form of data missing for particular months. We interpolate these by simply taking an average of the preceding and succeeding months¹. A further issue is the choice of poll when there are several polls in a month, as happens close to General Elections. When this occurs we use the poll which appears to have been carried out at the usual time of the month.

Partly as a response to the perceived failure to correctly forecast the outcome of the 1992 General Election, each of the polling organisations changed their sampling methods in the 1990s. ICM began telephone polling in November 1995 and Gallup in January 1997. MORI remained committed to quota sampling but changed its procedures.

The estimation procedure which we use for the univariate analysis has two stages. Firstly, we use the Schwartz information criterion to select an appropriate model of the $ARFIMA(p,d,q)$ class

$$\theta(L)(1-L^d)s_t = \varphi(L)u_t$$

¹ On rare occasions there are two successive missing values. These were adjusted in a rather *ad hoc* manner by looking at local trends. Given the sample sizes we do not think that these procedures induce any noticeable bias in the estimates.

where the autoregressive component, $\theta(L)$, is a lag polynomial of order p and the moving average component, $\phi(L)$, is a lag polynomial of order q . We compare models over a range of values for $p, q \leq 2, p + q \leq 2$. For all of the series considered here, the SIC chooses the pure fractional process, $ARFIMA(0, d, 0)$. We then estimate the model using a maximum likelihood estimator. Since there are quite a lot of apparent outliers in the data, suggesting that the underlying ‘shock’ process is fat-tailed, we assume that u_t has Student’s t distribution. This has the effect of giving less weight to observations which are relatively far from the centre of the distribution. Though it makes little difference to the estimates of d , we estimate the model in first differences, thereby obtaining an estimate of $1-d$ in the stationary process for Δs_t . We add 1 to get the results reported below. The multivariate models are estimated by Least Generalised Variance. All estimation and testing was carried out using James Davidson’s Time Series Modelling package. For details see Davidson (2005).

Results

In Table 1 we present estimates of the long memory parameter for Conservative and Labour support as measured by Gallup, MORI and ICM. For the Gallup data, we estimate d for two samples, the period up to the adoption of telephone polling and for the complete sample running from 1948 to 2000. The period of telephone sampling is too short to provide a useable sub-sample. For ICM we estimate d for the sample as a whole and for sub-samples corresponding to the period before telephone sample and the period after. For comparison purposes we break the MORI sample at the same value and estimate d for these.

The estimates presented in Table 1 vary somewhat across polling organisations but this appears to be the result of different sample sizes. Leaving the ‘telephone-polling’ sample to one side, the estimated value of d falls as the sample size increases. In addition, there is evidence that estimated d s for Conservative and Labour get closer as the sample size increases. The other main feature of the tables is the dramatically lower value of d estimated for the ‘telephone-polling’ sample. However, since the results for MORI and ICM are similar, this would appear not to be the result of the change in sampling method. To investigate further, we estimate rolling regressions of sample size 100 using the ‘Whittle’ estimator. The results are graphed in Figure 1. Note that this estimates the d for the first differences of the series. The vertical line in the graphs marks the start of telephone sampling by ICM. It is clear that the introduction of telephone polling is not associated with a change in the estimated d . There is a fall in the d for ICM but it occurs much later, at the start of 2001. The estimated d for the MORI series shows no sharp change but does fall steadily. The reasons for these results merits further investigation.

In Table 2 we present results from combining the available data to produce a continuous series from 1948 onwards. We use Gallup to the end of 1996 and either MORI or ICM from then onwards. The former series is consistent in the sense that it uses quota sampling throughout. However, as we have seen, the introduction of telephone sampling seems to have little or no effect. The two combined series produce effectively identical estimates of d for the Conservatives and for Labour and also suggest that a single value of d can be used to characterise both processes.

To test for equality between the various d s we estimate a four variable Vector $ARFIMA(0,d,0)$ model using the Gallup and MORI series over a common sample from August 1978 to December 2000. This exploits the strong correlations between the contemporaneous values of the series. The results are given in Table 3. The top part of the Table reports the estimated value of d for the four series and the middle part reports all possible pairwise equality tests. The numbers above the principal diagonal are the Wald test statistic, distributed as $\chi^2(1)$ - the upper figure in the pair - and the prob-value - the lower figure. The numbers below the principal diagonal are the constrained estimates of d . None of the pairwise nulls is rejected. At the bottom of the Table we report the Wald test for equality of all the d s. This null also fails to be rejected. Imposing the constraint we estimate the common value of d as 0.654.

Conclusion

In this paper we have used longer samples and additional poll series to extend the results of Byers, Davidson and Peel (1997) on long memory in support for the Conservative and Labour Parties in the UK. We find continuing support for the model though the estimates for our larger samples suggest somewhat smaller values of d than reported by BDP. For instance, the longer Gallup series produces estimates of 0.707 and 0.706 for Conservatives and Labour, respectively, compared with the earlier estimates of 0.779 and 0.726. We find that the move to telephone polling in the mid-1990s has no apparent effect on the estimated value of d for either party. Finally, we find that we cannot reject the

hypotheses that the parties share a common long memory parameter which we estimate at around 0.65

An interesting question raised by these results is why we find smaller d s. One possibility is that one requires a very large sample to remove ‘small sample’ bias in the estimator. Another, suggested by the graphs of the rolling regression estimates, is that d , itself, evolves through time or, pushing things back one step, that the distribution of the underlying $AR(1)$ parameters is changing. This is a matter for further investigation

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Table 1 : Univariate Estimates								
	Gallup		MORI			ICM		
	Conservative Support							
Sample	(i)	(ii)	(i)	(ii)	(iii)	(i)	(ii)	(iii)
Intercept	-0.109	-0.010	-0.013	-0.042	-0.013	-0.039	0.049	-0.028
s.e.	0.005	0.005	0.009	0.024	0.007	0.016	0.035	0.012
d	0.724	0.707	0.846	0.498	0.767	0.716	0.458	0.647
s.e.	0.039	0.038	0.057	0.074	0.044	0.112	0.109	0.101
AR(1)	0.626	0.802	0.313	0.015	0.484	1.117	0.049	1.707
LBQ(12)	21.303	15.080	16.693	15.897	11.536	6.752	10.264	6.674
ARCH(1)	3.865*	4.484*	1.513	0.376	0.991	0.010	1.556	0.860
	Labour Support							
Intercept	0.001	0.000	0.000	-0.010	-0.002	0.000	-0.020	-0.009
s.e.	0.005	0.004	0.008	0.012	0.006	0.011	0.013	0.009
d	0.715	0.706	0.800	0.624	0.744	0.774	0.571	0.682
s.e.	0.036		0.056	0.068	0.043	0.078	0.091	0.075
AR(1)	1.208	1.280	0.396	0.091	0.570	2.732	0.002	2.279
LBQ(12)	22.759*	19.218	6.623	7.545	7.513	11.203	13.001	12.578
ARCH(1)	4.566*	4.832	0.396	0.772	2.354	0.927	1.017	1.238
Sample Size	588	636	193	116	309	84	129	209

Notes

Sample Sizes:

Gallup: Jan 1948-Dec 1996, Jan 1948-Dec 2000

MORI: Aug 1979-Sept 1995, Oct 1995-April 2005, Aug 1979-April 2005

ICM: Oct 1987-Sept 1995, Oct 1995-April 2005, Oct 1995-April 2005

Residual Tests:

AR(1) is a conditional moment test for first order autocorrelations.

LBQ(12) is the Ljung-Box Q portmanteau test statistic for autocorrelation using lags 1 to 12.

ARCH(1) is a conditional moment test for neglected first order ARCH.

* denotes significance at 5%.

	Gallup/ICM		Gallup/MORI	
	CON	LAB	CON	LAB
Intercept	-0.010 0.004	-0.002 0.004	-0.009 0.004	0.000 0.004
<i>d</i>	0.710 0.038	0.710 0.035	0.731 0.032	0.733 0.032
AR(1)	0.677	1.011	0.417	0.391
LBQ(12)	17.291	16.509	15.393	12.054
ARCH(1)	6.9445*	2.532	11.2589*	7.8288*
Sample: Jan 1948-April 2005				n = 688

Notes: See Table 1.

<u>Table 3: Multivariate Estimates</u>				
<u>Unrestricted Vector-ARFIMA</u>				
	Gallup		MORI	
	CON	LAB	CON	LAB
<i>d</i>	0.648	0.626	0.690	0.654
s.e.	0.047	0.046	0.044	0.045
<u>Pairwise Equality Tests</u>				
	CON	LAB	CON	LAB
Gallup	CON	0.195	0.802	0.009
	LAB	0.637	0.370	0.924
MORI	CON	0.670	0.236	0.521
	LAB	0.651	0.670	0.483
<u>Restricted Vector-ARFIMA</u>				
<i>d</i>	0.654			
Wald Test for equality:			chisq(3)	1.511
			probval	0.679
Sample: Aug 1979 – Dec 2000				

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Figure 1: Rolling Regressions



